1   WHATIS CLAIMED IS:

2   1.   A system for controlling particle accelerators, comprising:

3   a distributed control system that further comprises:

4   a computing device operable to execute a first software

5   tool that identifies variable inputs and controlled

6   variables associated with the particle accelerator, wherein

7   at least one variable input is a manipulated variable

8   input, and wherein said first software tool is further

9   operable to determine relationships between said variable

10   inputs and said controlled variables; and

11   at least one input/output controller operable to monitor

12   said variable inputs and tune said manipulated variable to

13   achieve a desired controlled variable value.

14   2.   The system for controlling particle accelerators of Claim

15   1, wherein said relationships between said variable input

16   parameters and said controlled variables comprises a first

17   principle models wherein said first principle model is

18   dependent on said variable inputs.

19   3.   The system for controlling particle accelerators of Claim

20   1, further comprising neural networks utilized to identify

21   said variable inputs.

22   4.   The system for controlling within particle accelerators of

23   Claim 1, wherein said step of determining relationships

1   between said variable inputs and said controlled variables

2   utilizes a combination of physical models and empirical

3   methods.

4   5.   The system for controlling particle accelerators of Claim

5   4, wherein said physical models and empirical methods are

6   combined in series.

7   6.   The system for controlling particle accelerators of Claim

8   4, wherein said physical models and empirical methods are

9   combined in parallel.

10 7.   The system for controlling particle accelerators of Claim

11   4, wherein said physical model varies over an operating

12   range.

13 8.   The system for controlling particle accelerators of Claim

14   5, wherein said physical model is a function of said

15   variable inputs.

16 9.   The system for controlling particle accelerators of

17   claim 7, wherein said physical model comprises first

18   principle parameters which vary with said variable inputs,

19   wherein empirical methods comprise a neural network used to

20   identify first principle parameters values associated with

21   said variable inputs, and wherein said neural network

1   updates said first principle parameters with values

2   associated with said variable inputs.

3   10.   The system for controlling particle accelerators of Claim

4   9, wherein said neural network is trained.

5   11.   The system for controlling particle accelerators of Claim

6   9, wherein said neural network is trained according to at

7   least one method selected from the group consisting of:

8   gradient methods, back propagation, gradient-based

9   nonlinear programming methods, sequential quadratic

10   programming, generalized reduced gradient methods, and non-

11   gradient methods.

12   12.   The system for controlling particle accelerators of Claim

13   11, wherein gradient methods require gradients of an error

14   with respect to a weight and bias obtained by numerical

15   derivatives.

16   13.   The system for controlling particle accelerators of Claim

17   11, wherein gradient methods require gradients of an error

18   with respect to a weight and bias obtained by analytical

19   derivatives.

20   14.   The system for controlling particle accelerators of Claim

21   10, wherein said controlled variablecomprises a magnetic

22   field strength, shape, location and/or orientation and said

1   controlled variable comprises particle positions within

2   said particle accelerator.

3   15. The system for controlling nonlinear control problems

4   within particle accelerators of Claim 14, wherein said step

5   of tuning said manipulated variable comprises adjusting a

6   connector magnet and/or quadrupole magnet.

7   16. A dynamic controller for controlling the operation of a

8   particle accelerator by predicting a change in the dynamic

9   variable input values to the process to effect a change in

10   the output of the particle accelerator from a current

11   output value at a first time to a different and desired

12   output value at a second time to achieve more efficient

13   collisions between particles, comprising:

14   a dynamic predictive model for receiving the current

15   variable input value, wherein said dynamic predictive model

16   changes dependent upon said input value, and the desired

17   output value, and wherein said dynamic predictive model

18   produces a plurality of desired controlled variable values

19   at different time positions between the first time and the

20   second time to define a dynamic operation path of the

21   particle accelerator between the current output value and

22   the desired output value at the second time; and

1   an optimizer for optimizing the operation of the dynamic

2   controller over a plurality of the different time positions

3   in accordance with a predetermined optimization method that

4   optimizes the objectives of the dynamic controller to

5   achieve a desired path, such that the objectives of the

6   dynamic predictive model vary as a function of time.

7   17. The dynamic controller of claim 16, wherein said dynamic

8   predictive model comprises:

9   a dynamic forward model operable to receive variable input

10   values at each of said time positions and map said variable

11   input values to components of said dynamic predictive model

12   associated with said received variable input values in

13   order to provide a predicted dynamic output value;

14   an error generator for comparing the predicted dynamic

15   output value to the desired output value and generating a

16   primary error value as the difference for each of said time

17   positions;

18   an error minimization device for determining a change in

19   the variable input value to minimize the primary error

20   value output by said error generator;

21   a summation device for summing said determined variable

22   input change value with an original variable input value,

23   which original variable input value comprises the variable

24   input value before the determined change therein, for a

1   plurality of time position to provide a future variable

2   input value as a summed variable input value; and

3   a controller for controlling the operation of said error

4   minimization device to operate under control of said

5   optimizer to minimize said primary error value in

6   accordance with said optimization method.

7   18. A method for controlling particle accelerators, comprising

8   the steps of:

9   identifying variable inputs and controlled variables

10   associated with the particle accelerator, wherein at least

11   one variable input parameter is a manipulated variable;

12   determining relationships between said variable inputs and

13   said controlled variables wherein said relationship

14   comprises models, and wherein parameters within said model

15   are dependent on said variable inputs; and

16   tuning said manipulated variable to achieve a desired

17   controlled variable value.

18   19.   The method of Claim 18, wherein said step of

19   identifying parameters utilizes neural networks to identify

20   said parameters.

21 20. The method of Claim 18, wherein said step of identifying

22   parameters utilizes neural networks that identify said

23   parameters when an operating region changes.

1 21. The method of Claim 18, wherein said step of identifying

2   parameters utilizes neural networks that identify said

3   parameters.

4 22. The method of Claim 18, wherein said step of determining

5   relationships between said variable inputs and said

6   controlled variables utilizes a combination of physical

7   models and empirical methods.

8 23. The method of Claim 22, wherein said physical models and

9   empirical methods are combined in series.

10 24. The method of Claim 22, wherein said physical models and

11   empirical methods are combined in parallel.

12 25. The method of Claim 22, wherein said physical model varies

13   over an operating range.

14 26. The method of Claim 25, wherein said physical model is a

15   function of said variable inputs.

16 27. The method of Claim 26, wherein said physical model

17   comprises first principle parameters which vary with said

18   variable inputs, wherein empirical methods comprise a

19   neural network used to identify first principle parameter

20   values associated with said variable inputs , and wherein

1   said neural network updates said first principle parameters

2   with values associated with said variable inputs.

3   28. The method of Claim 27, wherein said neural network is

4   trained.

5   29. The method of Claim 28, wherein said neural network is

6   trained according to at least one method selected from the

7   group consisting of gradient methods, back propagation,

8   gradient-based nonlinear programming (NLP) methods,

9   sequential quadratic programming, generalized reduced

10   gradient methods, and non-gradient methods.

11 30. The method of Claim 29, wherein gradient methods require

12   gradients of an error with respect to a weight and bias

13   obtained by either numerical derivatives or analytical

14   derivatives.

15 31. The method of Claim 18, wherein said manipulated variable

16   comprises a magnetic field strength, shape, location and/or

17   orientation and said controlled variable comprises particle

18   positions within said particle accelerator.

19 32. The method of Claim 31, wherein said step of tuning said

20   manipulated variable comprises adjusting a connector

21   magnet.

1   33. The method of Claim 31, wherein said step of tuning said

2   manipulated variable comprises adjusting and quadrapole

3   magnet.

4   34. The method of Claim 31, wherein said step of tuning said

5   manipulated variable comprises adjusting a connector magnet

6   and quadrapole magnet.